

Locally Linear Regression:

There is another local method, locally linear regression, that is thought to be superior to kernel regression. It is based on locally fitting a line rather than a constant. Unlike kernel regression, locally linear estimation would have no bias if the true model were linear. In general, locally linear estimation removes a bias term from the kernel estimator, that makes it have better behavior near the boundary of the x 's and smaller MSE everywhere.

To describe this estimator, let $K_h(u) = h^{-r}K(u/h)$ as before. Consider the estimator $\hat{g}(x)$ given by the solution to

$$\min_{g, \beta} \sum_{i=1}^n (Y_i - g - (x - x_i)' \beta)^2 K_h(x - x_i).$$

That is $\hat{g}(x)$ is the constant term in a weighted least squares regression of Y_i on $(1, x - x_i)$, with weights $K_h(x - x_i)$. For

$$Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}, X = \begin{pmatrix} 1 & (x - x_1)' \\ \vdots & \vdots \\ 1 & (x - x_n)' \end{pmatrix}$$

$$W = \text{diag}(K_h(x - x_1), \dots, K_h(x - x_n))$$

and e_1 a $(r + 1) \times 1$ vector with 1 in first position and zeros elsewhere, we have

$$\hat{g}(x) = e_1'(X'WX)^{-1}X'WY.$$

This estimator depends on x both through the weights $K_h(x - x_i)$ and through the regressors $x - x_i$.

This estimator is a locally linear fit of the data. It runs a regression with weights that are smaller for observations that are farther from x . In contrast, the kernel regression estimator solves this same minimization problem but with β constrained to be zero, i.e., kernel regression minimizes

$$\sum_{i=1}^n (Y_i - g)^2 K_h(x - x_i)$$

Removing the constraint $\beta = 0$ leads to lower bias without increasing variance when $g_0(x)$ is twice differentiable. It is also of interest to note that $\hat{\beta}$ from the above minimization problem estimates the gradient $\partial g_0(x)/\partial x$.

Like kernel regression, this estimator can be interpreted as a weighted average of the Y_i observations, though the weights are a bit more complicated. Let

$$S_0 = \sum_{i=1}^n K_h(x - x_i), S_1 = \sum_{i=1}^n K_h(x - x_i)(x - x_i), S_2 = \sum_{i=1}^n K_h(x - x_i)(x - x_i)(x - x_i)'$$

$$\hat{m}_0 = \sum_{i=1}^n K_h(x - x_i)Y_i, \quad \hat{m}_1 = \sum_{i=1}^n K_h(x - x_i)(x - x_i)Y_i.$$

Then, by the usual partitioned inverse formula

$$\begin{aligned} \hat{g}(x) &= e_1' \begin{bmatrix} S_0 & S_1' \\ S_1 & S_2 \end{bmatrix}^{-1} \begin{pmatrix} \hat{m}_0 \\ \hat{m}_1 \end{pmatrix} = (S_0 - S_1' S_2^{-1} S_1)^{-1} (\hat{m}_0 - S_1' S_2^{-1} \hat{m}_1) \\ &= \frac{\sum_{i=1}^n a_i Y_i}{\sum_{i=1}^n a_i}, \quad a_i = K_h(x - x_i) [1 - S_1' S_2^{-1} (x - x_i)] \end{aligned}$$

It is straightforward though a little involved to find asymptotic approximations to the MSE. For simplicity we do this for scalar x case. Note that for $g_0 = (g_0(x_1), \dots, g_0(x_n))'$,

$$\hat{g}(x) - g_0(x) = e_1' (X' W X)^{-1} X' W (Y - g_0) + e_1' (X' W X)^{-1} X' W g_0 - g_0(x).$$

Then for $\Sigma = \text{diag}(\sigma^2(x_1), \dots, \sigma^2(x_n))$,

$$\begin{aligned} E [(\hat{g}(x) - g_0(x))^2 | x_1, \dots, x_n] &= e_1' (X' W X)^{-1} X' W \Sigma W X (X' W X)^{-1} e_1 \\ &\quad + [e_1' (X' W X)^{-1} X' W g_0 - g_0(x)]^2 \end{aligned}$$

An asymptotic approximation to MSE is obtained by taking the limit as n grows. Note that we have

$$n^{-1} h^{-j} S_j = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i) [(x - x_i)/h]^j$$

Then, by the change of variables $u = (x - x_i)/h$,

$$E [n^{-1} h^{-j} S_j] = E [K_h(x - x_i) ((x - x_i)/h)^j] = \int K(u) u^j f_0(x - hu) du = \mu_j f_0(x) + o(1).$$

for $\mu_j = \int K(u) u^j du$ and $h \rightarrow 0$. Also,

$$\begin{aligned} \text{var}(n^{-1} h^{-j} S_j) &\leq n^{-1} E [K_h(x - x_i)^2 ((x - x_i)/h)^{2j}] \leq n^{-1} h^{-1} \int K(u)^2 u^{2j} f_0(x - hu) du \\ &\leq C n^{-1} h^{-1} \rightarrow 0 \end{aligned}$$

for $nh \rightarrow \infty$. Therefore, for $h \rightarrow 0$ and $nh \rightarrow \infty$

$$n^{-1} h^{-j} S_j = \mu_j f_0(x) + o_p(1).$$

Now let $H = \text{diag}(1, h)$. Then by $\mu_0 = 1$ and $\mu_1 = 0$ we have

$$n^{-1} H^{-1} X' W X H^{-1} = n^{-1} \begin{bmatrix} S_0 & h^{-1} S_1 \\ h^{-1} S_1 & h^{-2} S_2 \end{bmatrix} = f_0(x) \begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix} + o_p(1).$$

Next let $\nu_j = \int K(u)^2 u^j du$. Then by a similar argument we have

$$h \cdot \frac{1}{n} \sum_{i=1}^n K_h(x - x_i)^2 [(x - x_i)/h]^j \sigma^2(x_i) = \nu_j f_0(x) \sigma^2(x) + o_p(1).$$

It follows by $\nu_1 = 0$ that

$$n^{-1} h H^{-1} X' W \Sigma W X H^{-1} = f_0(x) \sigma^2(x) \begin{bmatrix} \nu_0 & 0 \\ 0 & \nu_2 \end{bmatrix} + o_p(1).$$

Then we have, for the variance term, by $H^{-1} e_1 = e_1$,

$$\begin{aligned} & e_1' (X' W X)^{-1} X' W \Sigma W X (X' W X)^{-1} e_1 \\ = & n^{-1} h^{-1} e_1' H^{-1} \left(\frac{H^{-1} X' W X H^{-1}}{n} \right)^{-1} \frac{h H^{-1} X' W \Sigma W X H^{-1}}{n} \left(\frac{H^{-1} X' W X H^{-1}}{n} \right)^{-1} H^{-1} e_1 \\ = & n^{-1} h^{-1} \left[\left(e_1' \begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix}^{-1} \begin{bmatrix} \nu_0 & \nu_1 \\ \nu_1 & \nu_2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix}^{-1} e_1 \right) \frac{\sigma^2(x)}{f(x)} + o_p(1) \right]. \end{aligned}$$

Assuming that $\mu_1 = 0$ as usual for a symmetric kernel we obtain

$$e_1' (X' W X)^{-1} X' W \Sigma W X (X' W X)^{-1} e_1 = n^{-1} h^{-1} \left(\nu_0 \frac{\sigma^2(x)}{f(x)} + o_p(1) \right).$$

For the bias consider an expansion

$$g(x_i) = g_0(x) + g_0'(x)(x_i - x) + \frac{1}{2} g_0''(x)(x_i - x)^2 + \frac{1}{6} g_0'''(\bar{x}_i)(x_i - x)^3.$$

Let $r_i = g_0(x_i) - g_0(x) - [dg_0(x)/dx](x_i - x)$. Then by the form of X we have

$$g = (g_0(x_1), \dots, g_0(x_n))' = g_0(x) W e_1 - g_0'(x) W e_2 + r$$

It follows by $e_1' e_2 = 0$ that the bias term is

$$\begin{aligned} & e_1' (X' W X)^{-1} X' W g - g_0(x) = e_1' (X' W X)^{-1} X' W X e_1 g_0(x) - g_0(x) \\ & + e_1' (X' W X)^{-1} X' W X e_2 g_0'(x) + e_1' (X' W X)^{-1} X' W r = e_1' (X' W X)^{-1} X' W r. \end{aligned}$$

Recall that

$$n^{-1} h^{-j} S_j = \mu_j f_0(x) + o_p(1).$$

Therefore

$$\begin{aligned}
& n^{-1}h^{-2}H^{-1}X'W((x - X_1)^2, \dots, (x - X_n)^2)' \frac{1}{2} \\
&= \begin{pmatrix} n^{-1} & h^{-2} & S_2 \\ n^{-1} & h^{-3} & S_3 \end{pmatrix} \frac{1}{2}g_0''(x) = f_0(x) \begin{pmatrix} \mu_2 \\ \mu_3 \end{pmatrix} \frac{1}{2}g_0''(x) + o_p(1).
\end{aligned}$$

Also, by $g_0'''(\bar{x}_i)$ bounded

$$\begin{aligned}
& \left\| n^{-1}h^{-2}H^{-1}X'W \left((x - x_1)^3 g_0'''(\bar{x}_1), \dots, (x - x_n)^3 g_0'''(\bar{x}_n) \right)' \right\| \\
& \leq C \max \left\{ n^{-1}h^{-2} \sum_i K_h(x - x_i) |x - x_i|^3, n^{-1}h^{-2}S_4 \right\} \longrightarrow 0.
\end{aligned}$$

Therefore, we have

$$\begin{aligned}
e_1'(X'WX)^{-1}X'Wr &= h^2 e_1' H^{-1} \frac{(H^{-1}X'WXH^{-1})^{-1}}{n} \cdot \frac{h^{-2}H^{-1}X'Wr}{n} \\
&= \frac{h^2}{2} g_0''(x) e_1' \begin{pmatrix} 1 & 0 \\ 0 & \mu_2 \end{pmatrix}^{-1} \begin{pmatrix} \mu_2 \\ \mu_3 \end{pmatrix} = \frac{h^2}{2} g_0''(x) \mu_2.
\end{aligned}$$

Exercise: Apply analogous calculation to show kernel regression bias is

$$\mu_2 h^2 \left(\frac{1}{2} g_0''(x) + g_0'(x) \frac{f_0'(x)}{f_0(x)} \right)$$

Notice bias is *zero* if function is linear.

Combining the bias and variance expression, we have the following form for asymptotic MSE:

$$\frac{1}{nh} \nu_0 \frac{\sigma^2(x)}{f_0(x)} + \frac{h^4}{4} g_0''(x)^2 \mu_2^2.$$

In contrast, the kernel MSE is

$$\frac{1}{nh} \nu_0 \frac{\sigma^2(x)}{f_0(x)} + \frac{h^4}{4} \left[g_0''(x) + 2g_0'(x) \frac{f_0'(x)}{f_0(x)} \right]^2 \mu_2^2.$$

Bias will be much bigger near boundary of the support where $f_0'(x)/f_0(x)$ is large. For example, if $f_0(x)$ is approximately x^α for $x > 0$ near zero, then $f_0'(x)/f_0(x)$ grows like $1/x$ as x gets close to zero. Thus, locally linear has smaller boundary bias. Also, locally linear has no bias if $g_0(x)$ is linear but kernel obviously does.

Simple method is to take expected value of MSE.